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The impact of integrated aquaculture–agriculture on small-scale farms in Southern Malawi

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Abstract

Sustainable agricultural intensification is an urgent challenge for Sub-Saharan Africa. One potential solution is to rely on local farmers' knowledge for improved management of diverse on-farm resources and integration among various farm enterprises. In this article, we analyze the farm-level impact of one recent example, namely the integrated aquaculture–agriculture (IAA) technologies that have been developed and disseminated in a participatory manner in Malawi. Based on a 2004 survey of 315 respondents (166 adopters and 149 nonadopters), we test the hypothesis that adoption of IAA is associated with improved farm productivity and more efficient use of resources. Estimating a technical inefficiency function shows that IAA farms were significantly more efficient compared to nonadopters. IAA farms also had higher total factor productivity, higher farm income per hectare, and higher returns to family labor.

JEL classification: O13, O32, O33, Q16, Q22

Keywords: Aquaculture; Malawi; Participatory research; Technical efficiency

1. Introduction

The agricultural sector in Sub-Saharan Africa (SSA) provides income and livelihood to the majority of people in the region but is characterized by low and in many locations decreasing productivity. Raising agricultural productivity is crucial to increase food production and to generate employment (Meier and Rauch, 2000).

Major limitations to agricultural productivity in SSA are degrading natural resources, limited and uncertain rainfall, and poor infrastructure and service support. Though a "sustainable agricultural intensification (SAI)" is most needed for SSA, a modernization of agriculture based on external inputs such as agrochemicals and improved high-yielding varieties (analog to the "green revolution" in Asia) may be out of reach for many locations in the near future (Kydd et al., 2004; Reardon et al., 1999).

Malawi is a small but densely populated country in SSA, with 52.4% of the population living below the poverty line (GoM, 2005). Agriculture is the major source of income for rural households (63.7%) but landholdings are small, and land productivity is generally low (Jamu and Chimatiro, 2004). Major constraints on land productivity include lack of irrigation and environmental degradation (Benson et al., 2002).

One potential approach to SAI involves agroecological programs that rely heavily on local farming knowledge, improved management of diverse on-farm resources, integration among various farm enterprises, and intensive use of organic inputs (Altieri et al., 1998; Sugunan et al., 2006). With the aim of providing a sustainable intensification option for small-scale farmers, the WorldFish Center, formerly known as ICLARM (International Center for Living Aquatic Resources Management), has been working in Malawi since the early 1980s with the Department of Fisheries, the University of Malawi, and the Ministry of Natural Resources and Environmental Affairs

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

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on participatory development and dissemination of integrated aquaculture–agriculture (IAA).

IAA, based on the concept of integrated resource management, utilizes synergies among subsystems resulting in higher farm productivity (Brummett and Noble, 1995; Sugunan et al., 2006). The general idea of IAA is that a small pond stocked with suitable fish and with materials available on the farm (such as crop residues and by-products) used as feed/pond fertilizer can be integrated in small-scale mixed-enterprises (Brummett and Noble, 1995). Rather than merely producing fish, the pond thus increases farm productivity by enabling synergistic interactions among different farm enterprises (see Edwards, 1998; Pant et al., 2005; Prein, 2002 for a detailed discussion of IAA technologies). The IAA research implemented in Malawi also comprises a new participatory approach to develop and transfer those technologies; information and ideas are exchanged interactively between farmers and researchers (Brummett and Noble, 1995).

The objectives of this article are to (1) assess the impacts of adopting IAA on small-scale farms in Malawi and (2) determine the major driving and inhibiting factors of technology adoption. The results provide valuable insights for other SSA countries with similar agroecological, socioeconomic, and institutional environments.

2. Data and methods

2.1. Data

A farm survey was conducted in early 2004 in six districts (Zomba West, Zomba East, Mulanje, Mwanza, Thyolo, and Mangochi), representing various agroecological and socioeconomic conditions, in the Southern part of Malawi.[1] In each site, a random sample of 30 IAA farmers and 30 non-IAA farmers was selected from a list of farmers kept by local extension workers. Out of 360 sample farmers, 315 (166 adopters and 149 nonadopters of IAA) were interviewed; the remaining farmers were not available. The survey covered information of the 2003/2004 season and data were collected on (1) socioeconomic farmer profiles; (2) farming environment; (3) sources of income and wealth status; (4) production systems; (5) inputs, output, and profitability of farming enterprises; (6) social and institutional environments; and (7) food and fish consumption. Some households could not provide detailed information on quantity and price of some inputs, but provided total expenditure by inputs. For technical efficiency analysis, we only used the 239 complete observations (119 adopters and 120 nonadopters).

The analysis presented in this article can be divided into two parts: the first part identifies factors determining adoption of IAA and thus establishes which technical, socioeconomic, institutional, and policy factors are associated with successful adoption. In part two, the impact of IAA adoption on farm productivity and income is assessed using overall technical efficiency (score), total farm productivity (total factor productivity score), profitability (US$/ha), and total farm income realized (US$/ha/year) as indicators.

2.2. Overall framework

Beginning with Schultz (1953) and Griliches (1958), numerous studies, conducted both *ex post* and *ex ante*, have examined the impacts of agricultural research on productivity and output growth for a wide range of commodities and countries (Alston et al., 1995; Maredia and Raitzer, 2006; Norton and Davis, 1981; Peterson and Hayami, 1977; Raitzer and Kelley, 2008). Alston et al. (1995), Masters et al. (1996), and Walker et al. (2008) provide guidelines on the conduct of impact assessment in agriculture. *Ex post* studies on the impact of agricultural research can be grouped into four general categories: (1) aggregate economic rate of return assessments (e.g., Alston et al., 2000; Evenson, 2001), (2) aggregate multidimensional impact assessments (e.g., Thirtle et al., 2003), (c) disaggregate economic rate of return assessments (e.g., Ahmed et al., 1994; Griliches, 1958), and (d) disaggregate multidimensional impact assessments (e.g., Adato and Meinzen-Dick, 2007; David and Otsuka, 1994; Hazell and Ramasamy, 1991; Renkow, 1994). A number of studies assess the impact of agricultural research in SSA (Ahmed et al., 1994; Bokonon-Ganta et al., 2002; Masters et al., 1998; Rukuni et al., 1998; Zeddies et al., 2001). A majority of these are disaggregate economic rate of return assessments. Learning from economic rate of return studies (aggregate or disaggregate level) is mainly relevant for resource allocation decisions. In contrast, multidimensional impact assessment studies have broader capacity for learning with expected results being potentially relevant to technology transfer and various other areas related to economic development (Walker et al., 2008).

In this article, we focus on analyzing disaggregate multidimensional farm-level impact of IAA in Southern Malawi. We aim at identifying the factors that determine IAA adoption at the household level and assessing the resulting changes in productivity and income. A broader analysis of IAA impact on the socioeconomic and national level as well as the nonmarket impacts can be found in Dey et al. (2007). Similar to previous multidimensional technology impact assessment studies (Walker et al., 2008), we have used mixed methods.

The overall hypothesis is that IAA leads to improved farm productivity through the improved use of natural capital and other inputs (Fig. 1). This is, first, because IAA practices are a technological innovation increasing the productivity of all inputs causing an upward shift in the production function. Second, IAA improves human and social capital, thus increasing farmers' efficiency in the use of both conventional and natural resource capital. This increase in technical efficiency due to higher human and social capital has an indirect impact on

[1] Poverty is more widespread in the Southern as compared to the Central and Northern Region of Malawi.

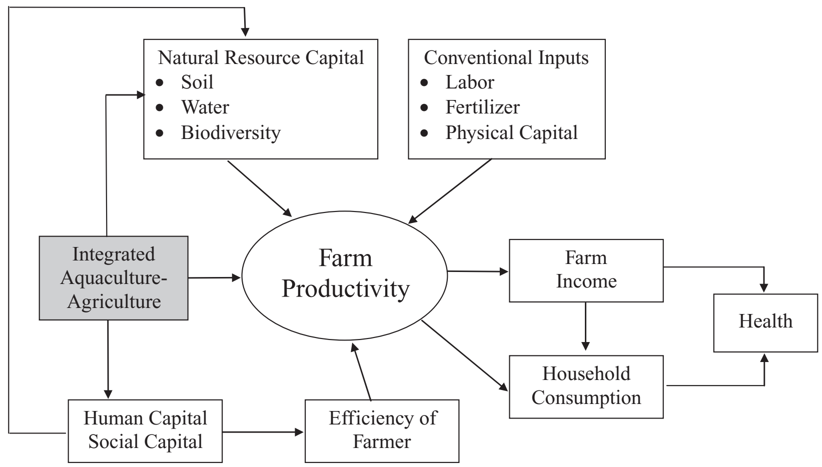

Fig. 1. Schematic diagram of impact of IAA on farm productivity and households' welfare.

yield (Fig. 1). Improvements in human and social capital result from interactive and participatory learning of new farming techniques, and from formation of social institutions such as fish farmers' clubs. The importance of learning-by-doing was earlier emphasized by Foster and Rosenzweig (1995); Bindlish and Evenson (1997); and Cameron (1999). Third, IAA improves the use and conservation of natural resource capital (such as soil, water, and biodiversity) through integrated resource management (i.e., recycling) as shown by Brummett and Costa-Pierce (2002).

Overall, IAA adoption impacts the production process through increased efficiency, improves the status of natural resources on the farm, and increases productivity. This means that IAA practices actually help to accumulate capital stocks (especially of natural, human, and social capital) and consequently increase the capital base at farmer's disposal. This is particularly important for the sustainability of the system (Pretty, 1999).

In addition to the impact outlined above, it is anticipated that (1) enhanced availability of fish as protein source will lead to increases in home consumption and (2) higher income will lead to more purchase of fish and other food. This results in improved nutritional and health status especially of children (Fig. 1). Subsequently, higher productivity of farmers can lead to consumer benefits due to reduced market prices of fish or increased employment opportunities on a more aggregated level.

2.3. Adoption analysis

We hypothesize that the adoption process is a continuum, as the intensity of technology use varies among the adopters (Rauniyar and Goode, 1996). Thus, a two-stage framework was applied to model the adoption process. In the first stage, we identify the factors affecting the probability of IAA adoption. In the second stage, we analyze the factors determining the intensity of IAA adoption (i.e., level of integration of different farm enterprises).

Various studies have used Tobit models for analyzing whether to adopt and how much to adopt, assuming that farmers take these two decisions jointly. The use of the Tobit model, however, restricts the directional effects to be the same for both the adoption decision and degree of integration decision. In the case of IAA adoption, a farmer in one region may be more likely to adopt IAA than farmers in other regions; however, her level of integration may be less than farmers in other regions due to differences in local environment and extension service. Given the nature of IAA, the decision to adopt (dig a pond) precedes the decision on the intensity level (integration) of IAA. Double hurdle models, as suggested by Cragg (1971), are often used for cases where both decisions—whether to adopt and how much to adopt—are made separately. In this case, a probit regression on adoption (using all observations) is followed by a truncated regression on the nonzero observations. In this article, we defined the intensity of IAA adoption as the fraction of the number of bioresource flows over the total number of enterprises per farm. As some of the early adopters will have zero integration of IAA, we cannot use the double hurdle method. An alternative to the double hurdle method is the Heckman two-step approach (Heckman, 1974), which also involves separate estimation of the participation and intensification decisions. Amemiya (1974) generalized the Heckman approach to include all observations in the second step by developing a measure of the inverse Mill's ratio (IMR) for the zero observations.

In the first stage, we estimate a logit model to determine the significance of various factors on the probability of adopting IAA (P)

$$P\left[Y_1 = 1\right] = \frac{1}{1 + e^{-\left(\beta_0 + \sum_i \beta_i X_i + \varepsilon\right)}}, \tag{1}$$

where Y_1 is a binary variable representing adoption with a value of 1 if the respondent is an IAA adopter and 0 if otherwise; X is a vector of explanatory variables (covering human and physical capital, social capital, and natural resources capital); β_i are the corresponding coefficients to be estimated; and ε denotes the error term.

In the second stage, we use Heckman's two-step procedure to analyze which factors determine the level of integration (i.e., the extent/intensity of IAA) that farmers are implementing on their farm. In the first step, we use the logit model (Eq. (1)) to calculate the IMR, the ratio of the value of the standard normal density function to the value of the standard normal cumulative distribution function, for all observation. In the second step, we include these IMRs as an additional explanatory variable for the IAA intensity function (Eq. (2)) and estimate it by ordinary least squares (OLS) method using all observations

$$\mathrm{IAA\_INT_i} = \mathrm{f(X, IMR_i, U_i)}, \qquad (2)$$

where IAA_INT is the ratio of the number of bioresource flows over the total number of enterprises per farm, X is the vector of explanatory variables used in Eq. (1), and IMR is the household specific inverse Mill's ratio.

2.4. Technical efficiency analysis

We hypothesize that IAA adoption increases technical efficiency[2] and thus leads to higher yield (due to direct and indirect effects), higher productivity, and ultimately higher income. This article evaluates the impact of IAA on the overall technical efficiency of the farm using the stochastic frontier approach. The level and determinants of technical efficiency (TE) were estimated to identify the causes of (in)efficiency and to analyze whether IAA farmers have higher efficiency. The system under investigation is small-scale farms with multiple enterprises.[3] Since the adoption of IAA technologies is expected to have an impact on other farm activities because of bioresource flows among enterprises and improved human capacity, we followed a whole farm approach rather than focusing on individual enterprises. The dependent variable in the stochastic production frontier model was thus the total observed farm output. In this article, we have used a variant of the stochastic function approach proposed by Battese and Coelli (1995), in which the technical inefficiency effects in a stochastic frontier are an explicit function of other farm-specific explanatory variables, and all parameters are estimated in a single-stage maximum likelihood (ML) procedure. The stochastic production frontier[4] is defined as

$$\mathrm{Ln}Y_i = \beta_0 + \sum_{j=1}^{6} \beta_j \mathrm{Ln}(X_{ij}) + (v_i - u_i), \qquad (3)$$

where subscript i refers to the i^{th} farmer; Ln represents the natural logarithm; Y is the observed farm output (US\$/ha); X_1 is the total seeding rate of all crop seeds combined (US\$/ha); X_2 is the preharvest labor use of family and hired labor (person days/ha); X_3 and X_4 are dummy variables for chemical and organic fertilizer application, respectively, which hold values of 1 if fertilizer is applied and 0 otherwise; X_5 is the amount of chemical fertilizers (mainly, nitrogen, phosphorous, and potassium) applied (kg/ha); and X_6 is the total amount of organic fertilizer applied in the farm (kg/ha). Technically, X_5 and X_6 are more correctly expressed by maximum (X_5, $1 - X_3$) and maximum (X_6, $1 - X_4$), respectively. LnX_5 (LnX_6) is the logarithm of chemical (organic) fertilizer rate, if chemical (organic) fertilizer was applied, and zero otherwise. This formulation of fertilizer variables (X_3, X_4, X_5, and X_6) takes explicit account of the fact that some farmers did not apply chemical and/or organic fertilizer.[5] If the fertilizer dummy variables (X_3 and X_4) are not included to account for intercept changes, estimates for the responsiveness of farm output to fertilizer application is biased (Battese, 1997).

Eq. (3) has two error terms: one (v_i) to account for random shocks (weather conditions, disease, measurement errors in the output variable, etc. and the combined effects of unobserved/uncontrollable inputs on production) and the other (u_i) to account for technical inefficiency in production. The v_i is a random error that is assumed to be independently and identically distributed (iid) $N(0, \sigma_v^2)$ and independent of the u_i; u_i is a nonnegative random variable. The model, defined by Eq. (3), is a stochastic frontier function because the random error (v_i) can be positive or negative and the output values are bounded above by the stochastic (random) variable, exp ($X_i\beta + v_i$).

It is assumed that u_i is independently distributed as a truncation (at zero) of the normal distribution function with mean μ_i that is defined as

$$\mu_i = \delta_0 + \sum_{i=1}^{7} \delta_i z_i, \qquad (4)$$

where z_i are farm-specific variables that may cause inefficiency, and δ_0 and all δ_i are coefficients to be estimated. The farm-specific characteristics are defined as following: Z_1 is a dummy variable for the type of respondents (1 if the farmer is practicing IAA and zero otherwise); Z_2 represents age as a proxy for experience of the operator (number of years); Z_3 represents the education of the farmer (number of years formal schooling); Z_4 represents the farm area (ha) as a proxy for income; Z_5 is a dummy variable for the gender of the household head (1 if male and zero otherwise); Z_6 is a credit dummy variable (1 if the farmer has access to credit and zero otherwise); and Z_7 is an extension dummy variable (1 if the farmer has access to extension services and zero otherwise).

[2] It is also important to assess the impact of IAA on allocative efficiency. We were unable to do so because of missing price data of inputs used.

[3] Given that we are essentially dealing with a multiple output technology, multiproduction distance function is an alternative approach. But we opted for the computation of technical efficiency using stochastic frontiers because of zero values in some of the outputs (i.e., not all farmers used all enterprises).

[4] For comprehensive reviews of frontier literature, readers are referred to Bauer (1990), Coelli (1995), and Greene (1997).

[5] Battese et al. (1996), Battese and Broca (1997), and Sharma and Leung (2000) have used a similar approach.

The farm-specific technical efficiencies (TE_i) are computed by taking the exponentiation of the negative of u_i, that is

$$TE_i = \exp(-u_i). \tag{5}$$

The estimation of technical efficiencies is based on the conditional expectation of $\exp(-u_i)$, given the model specifications (Coelli, 1996; Battese and Broca, 1997).

2.5. Total factor productivity analysis

Productivity improvement can be achieved in two ways: (1) by improving efficiency (i.e., farm operating more closely to the existing frontier) and (2) by improving the state of the technology (i.e., an outward shift in the production frontier). The most conventional measures of productivity and profitability are production (yield) and return (gross margin) per unit area. Such measures, however, fail to account for differences in input and output prices across farmer groups and sites. More importantly, partial productivity measures such as yield are not appropriate in a multi output–multi input setting, such as the IAA system that combines multiple enterprises. To overcome such limitations, this article uses the concept of interspatial total factor productivity to measure farm productivity and compare IAA and non-IAA farmers. Interspatial total factor productivity (TFP) refers to the ratio of total farm production given all the inputs used on the farm and is computed using the interspatial Tornqvist–Theil Index (Martinez-Cordero et al., 1999). The use of the concept of TFP allows us to capture the synergies between different subsystems and to account for positive or negative externalities to other farm enterprises or resources created by the production process.

The interspatial Tornqvist–Theil Index (TI) is defined as

$$\begin{aligned} TI_i = {} & 0.5 \sum_l \mathrm{Ln}\left[{Y_{il}}/{Y_l}\right](s_{yil} + s_{yl}) \\ & - 0.5 \sum_k \mathrm{Ln}\left[{X_{ik}}/{X_k}\right](s_{xik} + s_{xk}), \end{aligned} \tag{6}$$

where the subscript i refers to the i^{th} farmer, l refers to the l^{th} output (maize, vegetables, and other), k refers to the k^{th} input (seed, fertilizer, labor), Ln refers to the natural logarithm, Y_{il} is the quantity of output (kg/ha), Y_l is the average across farmers, X_{ik} is the quantity of input, s_{yil} is the share of the l^{th} output to the total gross return, s_{xik} is the share of the k^{th} input to the total input cost, and s_{yl} and s_{xk} are the average shares of the l^{th} output and k^{th} input, respectively. Exponentiation of TI_i gives the productivity difference between the i^{th} farmer and the average farmer (TFP$_i$), indicating how much more or less it would cost for a particular farmer i as compared to the average farmer to produce the same quantity of output per unit area using the same technology.

2.6. Impact of IAA on farm income

We assess the contribution of IAA to overall farm income using both nonparametric and econometric procedures. One of the methodological challenges for impact assessment studies is to deal with the attribution issue, and to establish causality between intervention and change. In our case, IAA adopters differ from nonadopters in characteristics that have not been observed and affect both the decision to adopt the technology and its outcome (e.g., ability or motivation). The mean differences in farm income between IAA adopters and nonadopters may be (partially) caused by farmers' characteristics rather than their IAA adoption status. To correct for this possible selection bias, we have used the nonparametric "propensity-score matching" (PSM) method (Becker and Ichino, 2002) and Heckman's two-step procedure (as discussed earlier).

The first step of the PMS approach was to estimate farmers' propensity scores based on their basic characteristics (i.e., characteristics unaffected by the choice of IAA adoption) using Eq. (1) (probability of adopting IAA). After farmers' propensity scores were estimated, the farmers are divided into groups with similar basic characteristics. Then adopters and nonadopters are compared within these groups.

For impact analysis, we then follow the so-called Heckman's two-step procedure. In this approach, first, the probability of being an IAA adopter is estimated using a logit model (Eq. (1)). Then, farm income (Eq. (7)) is regressed against a binary variable indicating IAA adoption, other household characteristics, and the IMR from the probit model. The IMR corrects the selection bias (see Greene, 2003; and Ravallion, 2005). The income function is defined as

$$\ln L_i = \beta_0 + \sum_{j=1}^{6} \beta_j X_{ij} + \beta_7 IMR + \mu_i, \tag{7}$$

where β_0, β_1, and all β_j are coefficients to be estimated; L is farm income per hectare; *IMR* is the household specific inverse Mill's ratio; X_{i1} is the IAA dummy variable; X_{i2} represents Ln of farm size (ha); X_{i3} represents Ln of nonfarm income; X_{i4} and X_{i5} are dummy variables for access to irrigation and credit, respectively; and X_{i6} represents education of the household head (number of years of formal education).

3. Adoption of integrated aquaculture–agriculture

Rogers (2003) argues that the diffusion of innovations depends on the characteristics, preferences, and environment of individual adopters. In other words, a farmer is expected to choose whether or not to adopt a technology based on the match between her assets, the technology's requirements, and her perception of that technology's suitability for her needs. The papers of Feder et al. (1985), Sunding and Zilberman (2001), and Doss (2006) offer comprehensive reviews of theoretical and empirical literature on the adoption of agricultural technologies.

Table 1
Key characteristics of IAA and non-IAA respondents

Variable	IAA farmers ($n = 166$)	Non-IAA farmers ($n = 149$)	All ($n = 315$)
Average age (years)***	45.51	39.88	42.85
Average household size (persons)	5.19	4.9	5.05
Average number of male adults	1.12	0.99	1.06
Average number of female adults	1.25	1.17	1.22
Average farm size (hectare)***	2.30	1.47	1.90
Average number of farm enterprises***	4.10	3.10	3.60
Average number of bioresource flows***	2.8	0.01	1.37
Male headed households (% HH)	68	44	55
Ownership of land (% HH)	97	97	97
Access to credit (% HH)	25	10	16
Access to extension services (% HH)	77	40	50
Access to irrigation (% HH)	39	49	45
Land type (% of total land)			
Homestead	22	30	26
Lowland	37	28	33
Upland	32	31	32
Wetland (dimba)	10	10	10
Topography (% of parcels)			
Flat	27	21	24
Gentle slope	57	62	59
Others	16	17	16
Source of water (%)			
Rainfall	75	78	76
Water course (natural)	9	8	9
Well	6	4	5
Others	10	10	10

Notes:
*, **, and *** indicate significant difference in group means at 0.1, 0.05, 0.01 level, respectively.
Statistical test for equality of mean was not conducted for variables expressed in percentage term.

The variables X_i that were included in our analysis to explain IAA adoption fall into the two general categories

Farm and farmer characteristics

- Age (years) of household (HH) head
- Gender of HH head (male = 1, female = 0)
- Education of household head (number years of schooling)
- Household members that were trained in IAA (number)
- Person–land ratio (total number of family members/hectare)
- Land area (hectare) as proxy of farm income
- Farm land tenure (ownership = 1, others = 0)

Biophysical and social environment

- Access to credit (access = 1, no access = 0)
- Access to extension service (access = 1, no access = 0)
- Access to irrigation (access = 1, no access = 0)
- Presence of (dimba) wetland area (present = 1, not present = 0)

Table 1 gives an overview of sample averages for these explanatory variables, showing any differences between IAA and non-IAA farmers. There is a significant difference in average age of the household heads in the survey sample, which is 45 and 40 years for IAA and non-IAA respondents, respectively. Older farmers may be more likely to undertake fish farming because they have the required skills, resources, and experience. The average family size of the IAA respondents was slightly larger (5.2 vs 4.9 persons) but the difference is not statistically significant. Also, the number of male and female adults is higher among the IAA respondents compared to the non-IAA respondents; though the differences between the two groups are not statistically significant. This has implications on the type and quantity of family labor available for aquaculture farming. Aquaculture production is generally undertaken by male-headed households individually or by female-headed households in groups. However, some individual female-headed households have fishponds.

The IAA respondents have a significantly larger average farm area than the non-IAA respondents.[6] The total farm area can include different natural resource types that can be considered as separate management units with distinct usage. Farmers distinguish homestead, lowland, upland, and wetland based on tenure, topography, soil type, and water supply (Lightfoot

[6] The farm sizes of the surveyed farmers are much larger than the average farm size in Southern Malawi (0.89 ha in 2004/5). In Malawi, marginal areas such as waterlogged depressions (*dambo*) have been utilized for IAA technologies (Brummett and Noble, 1995) and including these areas results in much larger farm size.

et al., 1993). The staple crop in Malawi is maize, but smallholder farming systems normally also comprise a variety of vegetable and fruits mainly for household consumption and to supply local markets. The IAA farmers have more land in the lowland compared to non-IAA respondents. Low-lying areas are particularly suitable as pond sites, because they have very shallow groundwater levels and are in many cases considered marginal land that is not used for agricultural production. The difference in access to flat land (gentle slopes) in absolute terms is statistically significant between IAA and non-IAA respondents. Such flat land is usually suitable for fishpond construction and operation as it is mainly associated with clay soils. A majority of both IAA and non-IAA respondents (97%) hold single ownership of the parcels that they farm. For both groups of respondents, rainfall is the primary source of water for farming enterprises and most water sources are seasonal in nature (Table 1).

The average number of bioresource flows among the IAA respondents was 2.8 (Table 1) and the maximum number was as high as 8 bioresource flows. The actual level of integration is primarily governed by the number of enterprises, their relative dimension and distance to each other and to fishpond and homestead. Within an IAA farming system, increasing levels of integration (i.e., material flows) are gradually achieved over time. This explains why 18% of IAA farmers who were at an early adoption stage did not have any bioresource flows.

The estimated adoption function (Eq. (1)) and IAA intensification function (Eq. (2)) are presented in Table 2. Results show that farmers who have access to extension services are more likely to adopt IAA, *ceteris paribus* (Table 2). This is not surprising and also holds true for the adoption of other knowledge intensive technologies such as livestock rearing, as shown in a recent study in Tanzania (Abdulai and Huffman, 2005). Also, the likelihood to adopt IAA is higher for older farmers with larger farm area[7] and a greater number of enterprises. Higher formal education did not lead to higher IAA adoption. However, once adopted, the level of education increased the level of integration of IAA practices. It needs to be stressed that the level of formal education might be far less relevant for adoption decisions than learning-by-doing, which might lead to a gradual intensification of IAA. In the existing literature, evidence of the relationship between formal education and agricultural technology adoption is mixed (Asfaw and Admassie, 2004; Lipton et al., 2002). Some studies conducted in developing countries (for example, Godoy et al., 1998, in Bolivia; Mukhopadhyay, 1994, in India; Njoku, 1990, in Nigeria) reveal that being educated does not necessarily influence agricultural technology adoption. Yirga et al. (1996) found that literacy is not significantly related to the probability of adopting improved wheat in Ethiopia, but positively and significantly related to the intensity of technology adoption.

Table 2
Determinants of IAA adoption

Method of estimation	Stage 1: Adoption (Eq. (1))		Stage 2: Level of integration (Eq. (2))	
	Logit Model		Two-step Heckman	
	Estimates	S.E.	Estimates	S.E.
Intercept	−2.25***	0.71	0.41074	0.48113
Age (years)	0.02**	0.01	0.0026	0.00303
Education of household head (years)	−0.12	0.09	0.05174*	0.029
Gender of household head (male = 1)	0.43	0.48	0.03342	0.14353
Persons in HH trained in IAA (number)	0.79***	0.25	−0.08299	0.06712
Extension dummy (access = 1)	1.01***	0.27	−0.19229	0.16444
Credit dummy (access = 1)	0.50	0.36	−0.03878	0.0992
Land area (hectare)	0.30**	0.13	0.02087	0.02012
Person–land ratio (number/hectare)	−0.01	0.02	0.02645***	0.00865
Dimba area dummy (present = 1)	−0.21	0.34	0.25346**	0.10512
Irrigation dummy (access = 1)	−0.30	0.27	0.24738***	0.08936
IMR			−0.34705	0.2803

Dep. Variable: Stage 1: 1 if IAA ($N = 166$); 0 otherwise ($N = 149$); Stage 2: Level of integration measured as the ratio of the number of bioresource flows over the total number of enterprises per farm ($N = 166 + 149 = 315$).
*Significant at $\alpha = 0.10$; **Significant at $\alpha = 0.05$; ***Significant at $\alpha = 0.01$.

At the same time, access to irrigation enables a higher intensity of adoption (Table 2). Similarly, as expected, the coefficient of the dimba dummy (presence of land with residual moisture or high water table) is significant and positive for the IAA intensification function. Ownership of dimba land enables farmers to practice integrated farming. The available land area is a significant explanatory variable in both stages, having a positive effect on IAA adoption and the level of integration. The person–land ratio positively affects the level of IAA integration, which highlights that IAA is a labor intensive technology. Land tenure was not included in the regression as most farmers owned the land they were cultivating, and the distance to markets could not be used as explanatory variable due to a large number of missing values and very high variation of distances stated within villages.

Additional factors that may affect the management of natural resources and thus the decision to adopt IAA practices are local marriage and inheritance patterns (Hansen et al., 2005), existing sociocultural norms (ICLARM and GTZ, 1991) and farmers' subjective perceptions of the characteristics of new technologies (Adesina and Baidu-Forson, 1995). In a recent study on IAA systems in Thailand, Pant et al. (2005) stress the importance of market access as precondition for the intensification of production.

[7] It needs to be emphasized that even these larger farms are still small-scale with per capita land holdings of around 0.4 hectares.

Table 3
Estimated stochastic frontier production and technical inefficiency functions

	Estimates	S.E.	Marginal effects
Stochastic production function			
Constant	3.187***	0.515	
Ln seed (US$/ha)	0.419***	0.047	0.419
Ln labor (person day/ha)	0.510***	0.108	0.510
Chemical fertilizer dummy	−0.230	0.242	−0.146
Organic fertilizer dummy	−1.406***	0.597	−0.500
Ln chemical fertilizer (kg/ha)	0.131***	0.055	0.131
Ln organic fertilizer (kg/ha)	1.555***	0.726	1.555
Technical inefficiency function			
Constant	0.291	0.537	
IAA practice dummy	−0.310**	0.162	−0.495
Age (y)	−0.007*	0.001	−0.909
Education (y)	−0.022	0.066	−0.135
Farm area (ha)	0.033	0.025	0.190
Male household head dummy	−0.534	0.472	−0.890
Access to credit dummy	0.089	0.277	0.043
Extension dummy	−0.224	0.167	−0.339
Variance parameters			
Σ^2	0.422***	0.056	
γ	0.813***	0.067	

*Significant at $\alpha = 0.10$; **Significant at $\alpha = 0.05$; ***Significant at $\alpha = 0.01$.
$N = 119$ (IAA) and 120 (non-IAA).

4. Impact on technical efficiency

We used the FRONTIER 4.1 package (Coelli, 1996) to calculate the maximum likelihood (ML) estimates of the parameters of the stochastic production functions defined by Eqs. (3) and (4), and the farm-specific TE defined by Eq. (5). In the process, the variance parameters of the livelihood function ($\sigma^2{}_u$ and $\sigma^2{}_v$) are expressed in terms of the parameterization: $\sigma^2 = (\sigma_u^2 + \sigma_v^2)$ and $\gamma = (\sigma_u^2/\sigma^2)$. The value of γ ranges from 0 to 1, with values close to 1 indicating that the deviations from the frontier are due mostly to technical inefficiency.

The production function defined in Eq. (3) is of Cobb-Douglas (CD) specification. We have tested the CD specification against a translog specification. The significance of the interaction and square terms was jointly tested using likelihood ratio (LR) tests. The value of the loglikelihood function of the CD specification is −228.99, while it is −223.75 for the translog specification. The estimated generalized likelihood-ratio (LR) statistic is 10.47 which is smaller compared to the critical value (chi-square statistic) of 18.31 at 95% level of significance and 10 degrees of freedom. This shows that there is no gain in using translog form over the CD form defined in Eq. (3).

The ML estimates of the frontier production function (Eq. (3)) and those of the technical inefficiency function[8] (Eq. (4)) are presented in Table 3. We have also computed the marginal effects to show the partial elasticities of the explanatory variables on both the frontier and the inefficiency functions (Table 3). The estimated marginal effects show relative importance of the different explanatory variables. All the estimated coefficients of nondummy variables are positive (i.e., $\beta_i \geq 0$) indicating that the estimated function is globally consistent (Sauer et al., 2006). All variables (except the chemical fertilizer dummy) included in the stochastic production function are highly significant (Table 3) indicating their importance in determining yield levels. The estimates of the stochastic frontier indicate that the elasticities of seed cost and labor use are approximately 0.42 and 0.51, respectively. Estimated elasticity of chemical fertilizer is about 0.15, whereas that of organic fertilizer is about 1.55.

Relatively large and significant elasticity of organic fertilizer implies positive contribution of IAA to farm productivity. The IAA system gives farmers an opportunity to increase recycling flows through integration among farm enterprises, and thereby to increase the use of organic fertilizer. Prior to engagement with the concept of IAA, farmers are often unaware of the nutrient management opportunities through bio-resource flows. Only one of the 149 sampled non-IAA farms recycles on-farm materials, that is, has some bioresource flows.

The value of the variance parameter, γ, associated with the variances in the stochastic production frontier is significant, suggesting that technical inefficiency does significantly influence the small-scale agriculture production in Malawi. Since the dependent variable in Eq. (4) is defined in terms of technical inefficiency, a farm-specific variable associated with the negative coefficient will have a positive impact on technical efficiency and vice versa. The estimated technical inefficiency function reveals that the dummy variable for IAA is negative and significant, indicating that on average IAA farmers are more technically efficient than non-IAA farmers. There are at least two reasons for this higher technical efficiency: first, IAA adopters use farm resources more efficiently because "an output from one subsystem in an integrated farming system which otherwise may have been wasted becomes an input to another subsystem resulting in a greater efficiency" (Edwards, 1998). Second, IAA adoption does increase human and social capital as a result of learning new input use techniques and subsequently experimenting with and adapting them to the specific on-farm conditions. Results also indicate that older farmers are more technically efficient than younger farmers, as they have more farming experience and had thus more time for the learning and adaptation process (Table 3).

Fig. 2 depicts the frequency distribution of the estimated TE scores. On average, the technical efficiency score of IAA farmers is 90%, while it is only 65% for non-IAA farmers. None of the IAA farmers has a technical efficiency score of less than 50%, while around 40% of the non-IAA farmers have a TE score lower than that. These figures reveal that with better production and social environments, such as those created through IAA and participatory extension approaches, poor farmers in Malawi can improve their efficiency substantially—despite

[8] The software FRONTIER 4.1 simultaneously estimates the parameters of the stochastic production frontier and the technical inefficiency model. Numerous papers use the FRONTIER 4.1 package and report technical inefficiency in this way, such as Battese et al. (1996); Wilson et al. (1998, 2001); Yao and Liu (1998); Sharma and Leung (2000); and Dey et al. (2005).

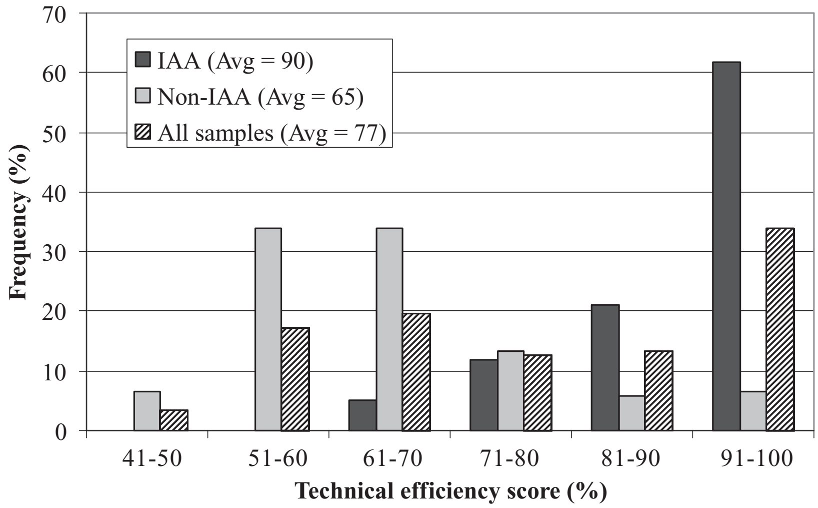

Fig. 2. Distribution of technical efficiency scores for IAA and non-IAA farmers.

Table 4
Comparison of farm profitability (US$/ha/year) and productivity

	By household type		Impact	Level of integration	
	IAA	Non-IAA	(%)	Low	High
Gross income	163	93	76	101	205
Total cost	67	51	30	54	74
Seed	14	10	32	11	16
Fertilizer	22	16	35	18	22
Manure	3	2	38	2	5
Labor[a]	28	22	25	23	32
Net income	96	41	134	47	131
TFP	1.33	1.20	11	1.18	1.52

$N = 166$ (IAA) and 149 (non-IAA).
[a]Labor was valued based on the ruling wage rates. The respondents were asked to indicate how much they would charge for the same amount of work if they were engaged in piecework. Where a household could not be engaged in piecework, they were asked how much they would have paid somebody to do the work.

being poor.[9] These results are consistent with findings of Arjumanara et al. (2004) and Dey et al. (2005) who have reported TE scores of more than 85% for small-scale fish farmers in various Asian countries. It is, however, important to emphasize that higher TE of farmers in utilizing a particular technology may not be enough for rapid dissemination of that technology. As discussed earlier, favorable biophysical conditions, and an enabling socioeconomic environment are important prerequisites for technology adoption.

5. Impact on productivity, farm income, and profitability

The TFP Index presented in Table 4 reveals that on average, IAA farmers in the Southern Region of Malawi are 11% more productive than non-IAA farmers (TFP of 1.33 for IAA farmers versus 1.20 for non-IAA farmers). Moreover, IAA farmers had a 134% higher income per hectare. Of special interest is the difference in productivity and profitability as the level of integration (number of bioresource flows between enterprises) increases. There is a positive association between productivity and profitability with the level of integration (Table 4). This can be attributed to the synergies between various farm enterprises (e.g., use of pond water for irrigation of plots) which lead to an increased cropping intensity and enable farmers to grow high value crops such as vegetables.

Moreover, IAA farmers had an annual farm income of US$185 which is about 1.6 times as much as non-IAA farmers' average of US$115. Around 73% of the total income of the IAA respondents was derived from farming compared to only 66% for non-IAA respondents—the difference is statistically significant at the 5% level. Fish culture directly contributed an average of US$21 (about 8%) to the annual farm income of IAA farmers (Fig. 3). While farm productivity and profitability as well as farm income were higher for IAA farmers, non-IAA respondents had higher off-farm incomes (earned from outside the homestead, e.g., employment or piecework) and more income from nonfarm activities (e.g., business within the homestead), though the difference is not statistically significant. IAA farmers spent an average of 72% of their time farming compared to 66% of the time spent by non-IAA respondents. Thus, on average, IAA farmers spent 24 person-days per hectare a year more than non-IAA farmers, for example, by recycling their produce or byproducts among the various enterprises; moving by-products between enterprises and the pond; managing the pond dikes; and stocking, harvesting, and selling fish. However, pond maintenance activities are normally scheduled in times of low labor demand from agricultural activities, thus smoothing the labor demand over the year and providing an alternative to off-farm employment during slack times for agricultural labor.

[9] For a recent discussion of Schultz's "poor but efficient" hypothesis, readers are referred to Abler and Sukhatme (2006).

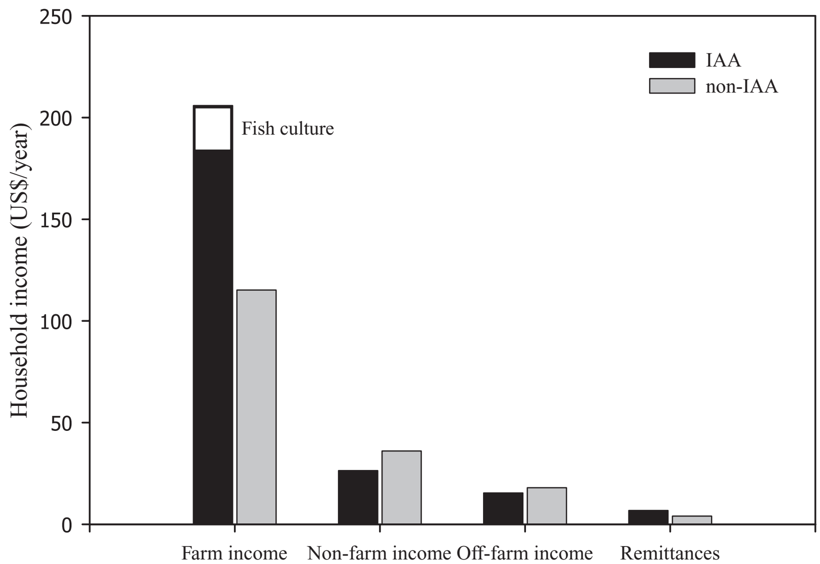

Fig. 3. Household income among IAA and non-IAA households.

Table 5
Effects of IAA on farm income matching estimate

Dependent variable	Matching estimates (nearest neighbor method)	S.E.
Ln (total farm income)	0.2208***	0..0396
Observation		
IAA adopter (treated)	166	
Non-IAA farmers (control)	149	

***Significant at $\alpha = 0.01$.

Table 6
Farm income function (Heckman's two-step estimation procedure)

	Estimates	S.E.	Partial elasticities
Intercept	8.520***	0.164	
IAA dummy (1 if practiced)	0.926***	0.269	0.488
Ln farm size (ha)	−0.748***	0.073	−0.748
Ln nonfarm income	0.019	0.012	0.019
Irrigation dummy (access to = 1)	0.373***	0.102	0.168
Credit dummy (access to = 1)	0.115	0.136	0.018
Education of household head (years of schooling)	0.026	0.033	0.053
Inverse Mill's Ratio	−0.243	0.174	
R^2	0.328		
F-value	21.360		

DV: Ln farm income per hectare; ***Significant at $\alpha = 0.01$.

As indicated in Section 3, the effect of IAA adoption on total farm income was estimated through two different methods, the nonparametric PSM technique and the econometric Heckman's two-step procedure. For the PSM technique, we have first used the estimated logit model (reported in Table 2) to predict propensity scores, and then followed two different matching methods, that is, the nearest neighbor method (NNM) and the kernel-based matching (KBM) method. The "nearest-neighbor" causal effect of IAA adoption on household farm income is highly significant and equal to about 0.22, which is the average difference between income of similar pairs of households but belonging to non-IAA adopter status (Table 5). Given that income is expressed in logarithmic form, the results imply that, on average, farm income of IAA adopters is almost 22% higher than income of nonadopters. The KBM yields similar results. Overall, PSM estimates show that IAA adoption has a positive and robust effect on household farm income in Malawi.

The estimated farm income function (Eq. (7)), based on Heckman's two-step procedure, is reported in Table 6. As the explanatory variables were expressed in different forms, we have also reported the marginal effects to show the partial elasticities. The positive sign of the coefficient for the IAA dummy indicates that on average, IAA adopters have higher net farm income than nonadopters. Moreover, access to irrigation increases per hectare farm income by 37%, *ceteris paribus*, while an increase of farm size by 1 hectare will decrease the per hectare farm income by 75%. While bigger size of land holding increases the probability of adopting IAA, it is inversely related to farm income per hectare. This finding is similar to the famous inverse relationship between farm size and productivity. It can be explained by labor usage, in that large areas are not cultivated as intensively as smaller ones. Given that IAA is very labor intensive, income per hectare will be lower for larger farms that are cultivated with less labor per hectare. The estimated coefficient of nonfarm income is positive, though statistically insignificant at the 10% level. This result implies that nonfarm activities do not negatively affect farm income in Southern Malawi and probably do not reduce labor availability for farm activities. This is crucial because the availability of seasonal labor is a decisive influence on farmers' technology choice and can be an important constraint for adoption even where land is in short supply as pointed out by Byerlee and Heisey (1996).

Total annual household income was almost 1.5 times higher for IAA respondents as compared to non-IAA respondents' average income (US$254 versus US$174, respectively). Results reported in this section reveal that adoption of IAA has increased farm income without significantly decreasing nonfarm and off-farm income. The productivity of family labor in IAA activities is higher than alternative opportunities of using family labor for off-farm activities, hence the overall return to labor from IAA is higher. Therefore, though non-IAA farmers generate a higher income from off-farm activities (renting out family labor), IAA farmers have higher overall income by using their family labor in IAA practices instead of selling it.

The increased farm income for IAA farmers came from (1) extra income from fish culture and (2) additional nonfish farm income. Farmers in the sample area who adopted IAA practices had a larger area for vegetable cultivation specially their homestead and in the uplands (Dey et al., 2007).

6. Summary and conclusion

Regression analyses show that extension contact, farmer training, better access to water, higher number of farm enterprises, and bigger farm size are associated with more adoption of IAA technologies in Southern Malawi. While it is the somewhat larger farmers that tended to adopt IAA, all farmers included in the sample had small holdings (an average farm size of 1.75 ha). Thus, IAA adoption is associated not only with a stronger capital base but also offers a safety-net effect in which farmers improve their access to food in general and protein in particular. However, access to at least some land is a precondition for IAA adoption. This is similar to many other agricultural innovations that landless people cannot adopt directly. Finally, the adoption by somewhat larger farmers suggest what has been observed in many other farming communities: marginal farmers tend to be more averse to taking risks and are therefore not likely to be among the first to adopt a new technology; instead, they follow a wait-and-see approach (e.g., Binswanger, 1980; Ghadim et al., 2005; Howitt and Taylor, 1993). Group or community-based approaches and training help small-scale farmers to adopt new technologies such as IAA more easily. One key element of the IAA approach is the participatory training of farmers and the technology dissemination through farmer groups. This has important implications for the sustainability of technology adoption. A study that evaluates the variation of economic performance of IAA adopters and nonadopters over a number of years (and diverse climatic conditions) could help to back-up the hypothesis that IAA adoption as a diversification of the existing farming system helps to reduce risk.

Once adopted, the IAA technology in southern Malawi is associated with total factor productivity (TFP) that is 11% higher for adopters than nonadopters, technical efficiency scores that are 35% higher, farm income per hectare that is 134% higher, and total farm income that is 60% higher. It is also noteworthy that the productivity of family labor in IAA activities on the farm is higher than the productivity of off-farm opportunities, that is, renting out family labor to other enterprises. Therefore, though non-IAA farmers had higher income from off-farm activities than IAA farmers, overall, IAA farmers had higher overall returns to family labor and thus higher household incomes. Regression analysis also shows that having higher nonfarm income is not associated with lower farm income in our sample.

The results highlight some of the benefits associated with freshwater fish farming in integration with agricultural activities. Other indirect benefits may arise that are not visible in these farm-level data, as shown by Dey et al. (2007). Such findings illustrate the potential of IAA to contribute to poverty reduction and improvements in livelihoods in Malawi and possibly other countries in SSA, which have similar conditions, especially Zambia, Mozambique, and also Cameroon, where IAA practices have recently been adopted.

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